

The Accuracy of School Classifications for the 2004 Accountability Cycle of the Kentucky Commonwealth Accountability Testing System

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Introduction

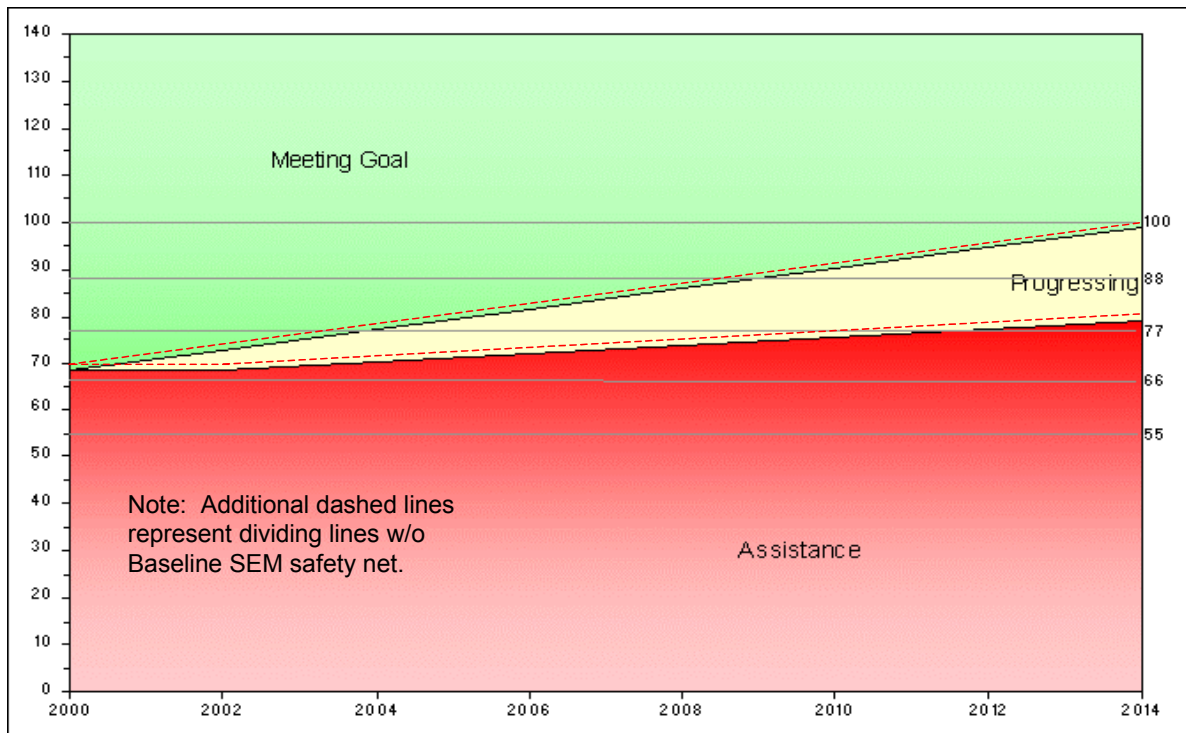
Kentucky's Commonwealth Accountability Testing System (CATS) was implemented in 1999 as a modification of the Kentucky Instructional Results Information System (KIRIS). Beginning with KIRIS, public schools in Kentucky have been classified by their successes in educating students. Both the KIRIS and CATS systems have significant consequences tied to schools' classifications making the accuracy of these classifications an important issue. Hoffman and Wise (2001) reported the accuracy of these classifications for the interim accountability cycle that bridged KIRIS and CATS. The present report presents the method used for calculating classification accuracy and the results for the first of the CATS long-term accountability cycles that are legislated to occur every two years beginning in 2002 and ending in 2014.

The report begins with an overview of the CATS long-term accountability model and then presents classification accuracy results for the first accountability cycle. Details of how the results were obtained then follow. Although the results are reasonably straightforward, computational details are complex and are mainly presented for technical readers.

CATS Long-term Accountability Model

The CATS long-term accountability cycle began with the school year of 1998-1999, which was the first year in which the newly revised Kentucky Core Content Test (KCCT) was administered. Because CATS testing occurs in the spring of each school year, we reference each year with the spring date only. Data from 1999 and 2000 constituted the "baseline" years upon which target scores for the period through 2014 have been set for every Kentucky school. These targets will be used to place schools into one of three categories: *Meeting Goal*, *Progressing*, and *Assistance*.

For each school, a School Growth Chart (see Figure 1) is constructed to depict school performance targets from 2000 through 2014. A "goal line" is initially plotted from the point on the chart representing a school's academic index for the baseline period and ending at the point that represents an academic index of 100 in the year 2014. The ending point is the statewide goal for all schools in 2014. The line is then adjusted downward to incorporate an allowance for measurement error. That is, the beginning of the line is actually plotted at one



Note: (Edited from a randomly selected school from the KDE website
http://www.kde.state.ky.us/oaa/implement/School_Report_Card/)

Figure 1. Modified School Growth Chart

standard error of measurement (SEM) below the school's calculated index and ends at one SEM below 100. The SEM refers to measurement error in the baseline accountability index.

Every school in Kentucky has a School Growth Chart indicating its prescribed trajectory, but the chart in Figure 1 has been modified from the ones presented to the schools by showing a goal line *without* measurement error allowance. At the end of every two-year accountability cycle, a school's new accountability index is compared to the solid line that divides the Meeting Goal (medium shaded or green if viewed electronically) area from the Progressing area (lighter shaded or yellow if viewed electronically). If the new Index score is at or above the line, then the school is improving close enough to the true-target rate (the dashed line) to be labeled Meeting Goal.

Figure 1 also shows two additional lines on the chart that divide Progressing and Assistance (darker shaded or red) areas. As defined by Kentucky regulation, the Assistance line begins with the baseline academic index at 2000, is sketched horizontally over to the year 2002 and is then extended to the point at the year 2014 representing an accountability index of 80. Like the goal line, the Assistance line used for actual classification is adjusted downward by one SEM. Again, the dashed line in Figure 1 (which is not presented to schools) shows the true line. The solid line that includes the safety net and divides the Progressing and Assistance areas in the chart is used to classify schools.

The distinction between the solid lines plotted on the chart with the built-in safety net and the dashed lines without the safety net is important for later classification accuracy computations. Throughout this report, we will refer to the “safety net” line and the “true” line to maintain this distinction.

Figure 1 is not the complete story for school classification. In addition to the accountability index scores, two additional criteria are applied before a school can be classified as meeting their goal. These criteria include meeting goals for (a) reducing the proportion of Novice students in their schools and (b) staying within maximum limits on the number of dropouts. At this time, neither of these criteria is considered in this analysis of school classification accuracy.

School Classification Accuracy Results

No assessment system is perfect, which means that an observed score, such as a school accountability index, is the product of two factors: true standing and measurement error. Although observed scores are known, true scores are not because the exact error in any given score is uncertain. Test reliability statistics, however, allow the estimation of how errors are distributed, making it possible to address the following two questions:

- What is the probability that a school is classified accurately? That is, what is the probability that a school's true scores places the school in the same accountability classification as the one assigned by its observed index scores?
- What is the probability that a school is incorrectly classified? That is, what are the odds that a school's true scores would result in the school being placed in a different accountability classification from the one assigned?

Table 1 presents a summary of classification accuracy results. The columns indicate school classifications considering only their accountability index scores. Ignored are special criteria concerning reduction in percentages of students classified as Novice and limits on school dropouts. *Italicized numbers* represent percentages of all students, so that their sum is 100% (within rounding). The ***bold italicized numbers*** represent the percent of schools expected to have true scores in a range that would yield the same accountability classification as the assigned classification. Thus, 45% of all schools were assigned “Meeting Goal” and are expected to have true classifications of “Meeting Goal.” Another 34% of all schools were assigned “Progressing” and are expected to have true classifications of “Progressing.” Finally, 3% of all schools are assigned Assistance and are expected to have true classifications of “Assistance.” The sum of the bold percentages, 82%, is the percentage of all schools whose true classifications are expected to match their assigned classifications. That is, school classification accuracy, for the system as implemented, is 82%.

Table 1
Classification Probabilities for 2004 School Accountability

Expected True Category	Assigned Category (Before Novice and Drop Criteria Applied)			Total Expected for True Classifications
	Meeting Goal	Progressing	Assistance	
Meeting Goal	45%	<i>1%</i>	<i>0%</i>	46%
Progressing	<i>11%</i>	34%	<i>1%</i>	46%
Assistance	<i>2%</i>	<i>3%</i>	3%	8%
% in Observed Class	58%	38%	4%	100%
Number in Obs Class	694	461	47	1202

Notes: Bold italics numbers indicate expected probabilities of accurate classifications. They sum to 82%. Only schools with data for all four years and with constant grade configurations are include in the analysis.

The bottom two rows of Table 1 show the percent of schools and total number with accountability index scores in each observed classification. In the right-most column, the table shows the percent of schools that would be expected in each classification if their true scores were knowable. Notice that more schools are actually assigned to the Meeting Goal category than are expected from our projections about true scores (58% vs. 46%). Conversely, fewer schools are assigned Assistance than are expected (4% vs. 8%). Part of this difference is the result of the application of the baseline safety net: Schools just under their true Goal or Assistance line are given the “benefit of the doubt” via the SEM allowance. As a result, the system places more schools into the Meeting Goal category than expected, but limits the chances that schools are classified too low because of measurement error.

Table 2 shows how accurately the accountability system would be if schools were classified without the baseline SEM safety net. These results are perhaps a better indication of measurement accuracy. Without the safety net, schools would be assigned to the category most likely to contain their true score. Therefore, overall accuracy, at 89% (the sum of the bold percentages in Table 2), is higher without the SEM safety net than with it. While seemingly paradoxical, this result was expected. Including the baseline safety net increases the total number of schools that are classified as Meeting Goal in order to reduce the risk of erroneously under-classifying schools. The result is that some schools are over-classified.

Table 2
Classification Probabilities for 2004 School Accountability without Baseline Safety Net

Expected True Category	Observed Category			Total Expected for True Classifications
	Without Applying Baseline SEM Safety Net			
	Meeting Goal	Progressing	Assistance	
Meeting goal	44%	2%	0%	46%
Progressing	5%	38%	3%	46%
Assistance	0%	1%	7%	8%
% in Observed Class	49%	41%	10%	100%
Number in Obs Class	586	499	117	1202

Notes: Bold italic numbers indicate expected probabilities of accurate classifications. They sum to 89%. Only schools with data for all four years and with constant grade configurations are include in the analysis.

Table 3 gives a more comprehensive picture by specifically identifying schools that benefited from the baseline safety net. In this table, six types of schools are identified:

1. Schools that are Meeting Goal with and without the baseline safety net (i.e., above the dashed goal line in Figure 1). These are labeled “MG & MG” in Table 3
2. Schools that are Meeting Goal with the safety net, but are Progressing without the safety net (i.e., schools between the solid and dashed goal lines). These are labeled “MG & P” in Table 3.
3. Schools that are Progressing with and without the baseline safety net for the Assistance line. These schools are below the solid goal line and above the dashed Assistance line in Figure 1 and are labeled “P & P” in Table 3.
4. Schools that are in Assistance with and without the baseline safety net (i.e., below the solid assistance line in Figure 1). These schools are labeled “A & A” (last column) in Table 3.
5. Schools that are Progressing with the safety net, but Assistance without the safety net (i.e., between the solid and dashed assistance lines). There schools are labeled “P & A.”
6. Schools that are in Assistance without the safety net, but are Meeting Goal with the safety net. These schools are labeled “MG & A.”

Table 3
Classification Probabilities with and without SEM Safety Net

Expected True Category	Classification with SEM Safety Net & without SEM Safety					
	MG & MG	MG & P	P & P	MG & A	P & A	A & A
Meeting Goal	89%	21%	1%	0%	0%	0%
Progressing	11%	79%	95%	14%	45%	14%
Assistance	0%	0%	4%	86%	55%	86%
% in Obs Class	100%	100%	100%	100%	100%	100%
Number in Obs Class	586	86	413	22	48	47

MG & MG = Meeting Goal with or without safety net.

MG & P = Meeting Goal with safety net but Progressing without it.

P & P = Progressing with or without safety net.

MG & A = Meeting Goal with safety net but Assistance without it.

P & A = Progressing with safety net but Assistance without it.

A & A = Assistance with or without safety net.

Table 3 shows percentages that total 100 within each column. The values express the likelihood of a given type of school having true index values that would result in a classification of Meeting Goal, Progressing, or Assistance. For example, schools above the dashed goal line (the “MG & MG” schools) have an 89% probability of being accurately classified as Meeting Goals and only a 11% probability of being truly in the Progressing category.

Comparing the “MG & P” to the “P & P” schools shows the effect of applying the safety net more explicitly. Again, the “MG & P” schools are those with index scores categorizing them as Progressing were it not for the safety net. These schools are most likely to have true scores that would place them in Progressing range (79%), but to protect the 21% that are likely to be in the true Meeting Goals range, all of these schools are classified as meeting their goals. That is, in order to avoid under-classifying 22% of these schools, 79% (100%-21%) of them are over-classified. In contrast, those schools below the solid goal line and above the solid assistance line (the “P & P” schools that are progressing with or without the safety net) have a 95% chance of truly being Progressing and only a 1% chance of truly being Meeting Goal. In other words, if a school has received a classification of Progressing, the odds are high that the school’s true standing, if known, would be in Progressing.

Schools in the final three columns all have scores that place them in Assistance without the safety net and in each case the probabilities are greater for them being in Assistance than any other category. In all three cases, there is no chance that a school classified as in Assistance without the safety net would actually be Meeting Goal. The “P & A” schools have a 45% chance of actually being Progressing and are granted this status by the safety net. “A & A” schools (assistance by both classifications) have an 86% probability of being accurately classified. For the schools that were classified as needing Assistance, chances are high that the classification is accurate.

Note that the safety net had to be set prior to the availability of complete data for 1999 through 2002 and was chosen to be one SEM in the baseline accountability index. The actual error is a function of measurement error in both baseline and end-of-cycle scores. The data in

Table 3, therefore, indicate how well the safety net actually protected schools from being misclassified. It seems to have functioned quite well in protecting individual schools from under classifications by measurement error.

These adjusted assignments may not be the best way to view the state learning progress as a whole. The safety net assignments indicate that 58% of schools are meeting their accountability goals. On the other hand, the expected true distributions (last column in Table 1 or 2) indicate that, if measurement error were removed, only about 46% of the schools meet the intended growth targets. A better estimate of state-wide school improvement is provided by the proportion of schools which would have been classified as Meeting Goal without the safety net factor (49%, according to Table 2). Note that this is up from a similar estimate of 40% (Hoffman & Wise, 2003) at the end of the 2002 accountability cycle.

A comparison between 2004 and 2002 shows some significant improvements in the classification process. As illustrated in Table 1 (e.g. School classifications prior to Novice and Drop criteria being applied), 45% of schools were classified as Meeting the Goal when they were expected to meet the goal, a significant increase from 2002 (34%). Overall, significantly more schools are classified as Meeting Goal in 2004 (58%) than in 2002 (49%). Without applying the Safety Net, significantly more schools are classified as Meeting Goal when expected to Meet Goal in 2004 (44%) than in 2002 (32%). Overall, more schools are being classified as Meeting Goal in 2004 (49%) than in 2002 (40%) while those being classified as Progressing has decreased in 2004 (41%) from 2002 (47%). Finally, when comparing classifications with and without the Safety Net, significantly more schools are being classified as meeting goal with and without the Safety Net in 2004 (89%) than in 2002 (80%). Also, significantly more schools are being classified as Progressing with and without the Safety Net in 2004 (95%) than in 2002 (90%). Table 4 shows that overall accuracy has increased from 2002.

Table 4. Total Percent of Schools Correctly Classified		
	Year	Percent *
Without SEM Safety Net	2002	82%
	2004	89%
With SEM Safety Net	2002	77%
	2004	82%

*Results indicate that the percentage of schools correctly classified has significantly increased between 2002 and 2004 when looking at both classification percentages both with and without the safety net.

Technical Details for Calculating School Classification Accuracy

The material that follows is technical in nature because of the large number of steps involved in reaching the results. This section is written for the technical audience. Some of the steps are straightforward. Other steps require the technical reader to think in some unusual ways. Much of this complexity is created by the need to consider the set of Kentucky schools not as a single population (which is normally the case when considering test statistics), but as representing multiple populations with measurement characteristics that differ by school size and by school grade configuration. An additional complication is that schools were classified based on index differences from both goal line projections and assistance line projections. The presentation begins with an overview of the procedure and then unfolds with details of the computations.

Overview

Student-level Kentucky Core Content Test scores are used to compute school accountability index scores. These tests are administered to selected grades such that all assessments are administered in typical elementary, middle, and high schools. Eight assessments are components of the KCCT and are prepared for Kentucky to assess achievement.¹ The eight assessments are augmented by a national norm-referenced test, the CTBS/5. Table 4 indicates the grades in which the assessments are administered. Kentucky Core Content Tests are indicated by subject.

Table 4
Assessments by Grade Level

Subject	Grade									
	3	4	5	6	7	8	9	10	11	12
Arts & Humanities			X			X			X	
Mathematics			X			X			X	
Practical Living/Vocational Studies			X			X		X		
Reading		X			X			X		
Science		X			X				X	
Social Studies			X			X			X	
On-demand Writing Prompt		X			X					X
Writing Portfolios		X			X					X
CTBS/5	X			X			X			

For each KCCT, students are classified into one of four achievement levels: Novice, Apprentice, Proficient, and Distinguished. The lower two levels, Novice and Apprentice, are subdivided into three sublevels (low, middle, and high) for of the four primary content disciplines (Reading, Mathematics, Science, and Social Studies). The point values used to calculate schools' average student achievement for primary content areas are shown in Table 5 and other areas in Table 6.

¹ As defined by the Kentucky Core Content Assessment and laid out by the Kentucky Core Content Test Blueprint (<http://www.kde.state.ky.us/oaa/valid/blueprint.asp>).

Table 5
Achievement Levels and Point Values for
Mathematics, Reading, Science, and Social
Studies

Achievement Level		Point Value
Distinguished		140
Proficient		100
Apprentice	High	80
	Middle	60
	Low	40
Novice	High	26
	Middle	13
	Low	0

Table 6
Achievement Levels and Point Values for
Arts & Humanities, Practical
Living/Vocational Studies, and Writing

Achievement Level		Point Value
Distinguished		140
Proficient		100
Apprentice		60
Novice	Attempt	13
	No attempt	0

CTBS/5 scores are included in the school accountability formula by converting percentiles to a scale similar to that for the KCCT. Specifically, student's quartiles (lowest to highest) are converted to scores of 0, 60, 100, and 140. These scores are used to compute schools' average CTBS/5 scores.

In addition to the KCCT and CTBS/5 data, schools also receive scores for a composite of non-academic factors such as attendance rate, retention rate, and dropout rate. Each school generates the non-academic data.

Given this array of data, estimating school classification accuracy can be conceptualized as a two-phase process that begins with the estimation of SEMs, or error variance, for schools' accountability cycle scores and is followed by transformation of error variance into the classification accuracy probabilities that appear in Tables 1, 2, and 3.

Estimating Standard Errors of Measurement

Schools' achievements are classified for CATS based on the difference between their end-of-cycle targets and their end-of-cycle accountability indexes. Therefore, the measurement error of most interest is the error in this difference. Error in the difference, however, is a function of the error in the baseline index (which is used to compute end-of-cycle targets) and the error in the end-of-cycle index. The estimation of these errors is complicated by a variety of factors.

First, school accountability index scores, for any cycle, are a weighted composite (weighted sum) of the scores from the various assessments administered in the schools. Therefore, the SEM for each accountability index (baseline and end-of-cycle) can be computed from SEMs for each assessment used in the computation (i.e., the KCCTs, CTBS/5, and non-academic indicators). As a result, the analyses deal with three types of SEMs:

- **Assessment SEMs** for school-level scores for Grade 4 Reading, Grade 10 Reading, Grade 9 CTBS/5, etc.

- **Accountability Index SEMs** for the baseline school index and each end-of-cycle index. Accountability SEMs are a function of assessment SEMs.
- **Classification SEMs**, which indicate the measurement error in the difference between observed accountability index and the goal for any particular accountability cycle. Classification SEMs are a function of accountability SEMs.

Generalizability Theory analyses, modeled on Yen (1997) and Miller (1999), are used to calculate assessment SEMs for the all except the non-academic indicators. The Generalizability analyses are identical to those used in calculating classification accuracy for the interim accountability model. Two Generalizability models were used: one for KCCTs with different forms in a given year and one for assessments in which all students had the same form. Details of these analyses are presented in Hoffman and Wise (2000b and 2001) and are repeated in the Technical Appendix of this report. In general, the model considers student scores as data points (in lieu of test items) but it is complicated by the fact that school scores for any end-of-cycle assessment are derived from different students for the two years in the cycle with these students taking multiple forms of the assessments that also differ across years. In other words, each student is like a test item, providing a single measure of the instructional capacity of the school. The test item analogy, however, is complicated by the two-year measurement period and by the potential for differences in test forms to impact how students function as a yardstick of school capacity. Variations in student, forms, and years can signal potential sources of measurement error. Further discussion is provided in the Appendix.

No method existed for estimating the error variance for the non-academic scores, so when computing classification accuracies for the interim accountability model Hoffman and Wise (2001) explored using the SEM values based on an assumed reliability of 1 (perfect reliability) and values based on an assumed reliability of 0 (total unreliability). It was determined that the estimate of overall school error was only slightly different for these two extreme assumptions. Therefore, we selected a conservative reliability estimate (.7) for the non-academic scores to use in calculations of school classification accuracy.

The second factor considered in estimating measurement error is the amount of data available for a particular school. Other things being equal, with more data there is less error. As a result of this principle, we expected large schools to be measured more accurately than small schools because their index scores are based on more students. Therefore, analyses of assessment SEMs were conducted on three representative school sizes: the lower third, the middle third, and the upper third.

These considerations mean that for any given cycle there are 81 assessment SEMs estimated by the Generalizability analyses: the 27 grade by assessment content areas (listed in Table 4) times the 3 school sizes.

A third consideration when estimating SEM is the fact that not all schools fit the typical elementary, middle, and high school model. In fact, accountability index SEMs had to be calculated for schools with 14 different grade configurations. (The exact combinations are presented later in Table A-6 in the Appendix.) Fortunately, accountability index SEMs are

computed from the separate grade/subject assessment SEM. Therefore, calculating accountability SEMs for schools with any particular grade configuration means including assessment SEMs for the assessments administered in the grades included in that configuration.

A fourth consideration is the requirement to estimate SEMs for a broad range of school sizes. In order to increase the precision of assessment SEM estimates for schools that do not fall in the representative sizes, an interpolation procedure was required to generate assessment SEM estimates for schools with anywhere from 10 to 500 students per grade.

Finally, schools were classified according to how their end-of-cycle accountability index fell in relation to their goal and assistance line targets for that cycle. Therefore, measurement error in the baseline and the end-of-cycle indexes were jointly considered. Computing classification accuracy involves consideration of the differences between a school's actual end-of-cycle index and the values specified by that school's true goal and assistance lines, i.e., when the lines are unadjusted by the baseline safety net. Carefully notice that schools actually will be classified according to where their accountability index falls in relation to the goal and assistance lines as plotted to include allowance for measurement error. For purposes of determining classification accuracy, however, schools' end-of-cycle accountability index must be compared to goal and assistance lines that are not adjusted for the potential error. In a sense, the classification accuracy analysis determines the extent to which the error allowance is protecting schools from inappropriately low classifications.

Note on multiple SEMs

Because of the complexity of the analysis process with its multiple levels of SEMs (assessment, accountability, and classification), it is easy to lose sight of the fact that within each of these levels, multiple SEMs are computed for varying school sizes and grade configurations. This is much more complex than calculating SEMs for a typical "test" in which one given set of observations (e.g., test items) in the assessment is the same for all subjects. In the case of school assessment, the number of observations in the assessment procedure depends on the number of grades in a school and the number of students within those grades. As a result, every school size and grade configuration combination has a specific set of assessment SEMs. Likewise, every school size and grade configuration combination has a specific accountability SEM. Finally, classification SEMs depend on school size in the baseline year, school size at the end-of-the cycle, and school configuration. Our classification SEM computations allow school size to change. On the other hand, a change in grade configuration invokes special regulations, typically involving the use of district-level scores. Therefore, our classification SEM computations exclude schools that change grade configurations.

Estimating Classification Accuracy Probabilities

Standard errors of measurement indicate expected variations of observed scores given a particular true score. Schools, however, have only their observed scores and are interested in how their true score might vary from their observed score. Our method for calculating classification accuracy is based on obtaining estimates of the distribution of true scores around observed scores. In our analyses of student classification accuracy (Hoffman and Wise, 2000a) and interim accountability classification accuracy (Hoffman and Wise, 2001), we applied

Bayes' Theorem and estimates of true score distributions to transform SEMs into estimates of the distribution of true scores around varying levels of observed scores.

Figure 2 illustrates the steps. First, classification SEMs are used to construct a matrix of the probabilities of observed scores given various possible true differences. The figure illustrates that these calculations are made for score intervals spreading from 0 in increments of .5 for possible true scores and observed scores. Using estimates of the probabilities of the various true scores, the top matrix in Figure 2 is converted to the bottom matrix of probabilities of various true score given potential observed scores. These operations are conducted twice: Once for differences around the goal line and once for differences around the assistance line. The shaded area in the lower table identifies accurate classifications.

Possible True Difference	Possible Observed Difference							
	<= etc.	-1.5 to -1.0	-1.0 to -.5	-.5 to 0	0 to .5	.5 to 1.0	1.0 to .5	etc. =>
<= etc.								
-1.5 to -1.0								
-1.0 to -.5								
-.5 to 0								
0 to .5								
.5 to 1.0								
1.0 to .5								
etc. =>								

Prob(Obs|True)

Via Prob(True)

Possible True Difference	Possible Observed Difference							
	<= etc.	-1.5 to -1.0	-1.0 to -.5	-.5 to 0	0 to .5	.5 to 1.0	1.0 to .5	etc. =>
<= etc.								
-1.5 to -1.0								
-1.0 to -.5								
-.5 to 0								
0 to .5								
.5 to 1.0								
1.0 to .5								
etc. =>								

Prob(True|Obs)

Figure 2. Schematic representation of matrices used in calculating classification accuracy.

Using the matrix of probabilities of true scores given observed scores, we can sum cells above and below 0 (the differently shaded areas) to estimate classification accuracy. The first step is to identify the column that contains a school's observed difference. Using the goal difference matrix, the probability of the school having a true meeting goal classification is the sum of the values in the identified column that are above the 0 true score. Using the assistance difference matrix, the probability of the school having a true assistance classification is the sum of the values in the identified column that are below the 0 true score. Since each school's true classification must be in Meeting Goal (MG), Assistance (A), or Progressing (P), the probability of the school's true classification being progressing can be calculated as:

$$\text{Prob}(P|\text{Observed Index}) = 1 - \text{Prob}(\text{MG}|\text{Observed Index}) - \text{Prob}(\text{A}|\text{Observed Index}).$$

Assessment SEM Computations

Assessment SEM are derived from Generalizability Theory analyses modified by a four-step process to consider varying school sizes:

- Identify representative target school sizes for Generalizability Theory analysis
- Create synthetic schools with target sizes
- Compute Generalizability Theory error estimates
- Interpolate assessment SEMs for school sizes 10 to 500 per grade.

Each is discussed in detail below.

Identifying Target School Sizes

The number of students within a school will affect the reliability of school-level scores; therefore, we begin assessment SEM computations using three representative school sizes. Because schools also differ in the number of grades they contain, and because the analysis begins with grade-level data, we defined school size by the average number of students in a grade. Small schools were identified as those in the smallest one-third of all schools, and the representative size was set at the median of that third, which is the 16.7th percentile of all schools. Similarly, medium size schools were those in the middle one-third and were represented by the 50th percentile of all schools. Finally, large schools were the largest one-third and were represented by the 83.3rd percentile of all schools.

The selection of representative school sizes was slightly complicated by the requirement to analyze data from different grades for two different years. That is, either the grade-level size for 2003 or 2004, or an average, could define school percentiles. Representative size was also affected by test form configuration. The KCCT is divided into multiple forms and we needed each form to be represented by an equal number of students in our analyses. Therefore, target sizes had to be adjusted to the nearest multiple of 12, which is the number of Arts & Humanities and Practical Living/Vocational Studies forms. By using 12 as the multiple, we also accommodated the 6 forms for the other subject areas.

Table 7 below shows the distribution of school size by grade and year, as computed for the KCCT during analyses of interim accountability classification accuracy. School sizes during the interim accountability cycle were the same as during the initial two years of the long-term accountability cycle. Therefore, school size targets determined for the interim classification accuracy analyses are usable for the present analysis. For reference, school sizes at the medians and the boundaries of the one-third size divisions are indicated, along with the maximum school size. Although there are 14 grade configurations for which accountability SEMs are calculated, schools with Grade 4 always include Grade 5, schools with Grade 7 always include Grade 8, and Grades 10, 11, and 12 are always combined. Hence, school size targets were set for Grade 4 and 5, Grade 7 and 8, and High School for the Kentucky Core Content Test. High School targets were set using only population data for Grade 10 and 11. We used these same school size targets when calculating end-of-cycle assessment SEMs because (1) school populations were not expected to shift sufficiently within the need to target a multiple of 12, and (2) an interpolation procedure was applied to cover the range of school sizes

Table 7
Identification of Representative School Sizes for Kentucky Core Content Tests

Grade	Year	School Sizes by Percentile					
		16.7th	33.3rd	50th	66.7th	88.3rd	Maximum
4	2003	30	45	59	75	96	246
4	2004	29	47	61	76	96	255
5	2003	28	44	57	73	89	290
5	2004	30	46	59	75	94	291
Grade 4/5 targets		24		60		96	
7	2003	35	70	126	191	246	438
7	2004	36	67	127	190	259	459
8	2003	36	71	133	191	256	430
8	2004	36	70	126	194	247	423
Grade 7/8 targets		36		120		240	
10	2003	61	115	179	228	298	624
10	2004	63	119	173	222	292	644
11	2003	65	110	164	202	258	563
11	2004	65	110	163	206	261	518
High School target		60		168		240	

Table 8 presents targets for CTBS/5 grades derived the same way as described above.

Table 8
Identification of Representative School Sizes for CTBS/5

Grade	Year	School Sizes by Percentile					
		16.7 th	33.3rd	50th	66.7th	88.3rd	Maximum
3	2003	31	47	63	79	105	275
3	2004	31	46	62	80	106	254
Grade 3 targets		24		60		96	
6	2003	25	40	59	98	222	449
6	2004	25	40	59	101	228	383
Grade 6 targets		24		60		180	
9	2003	33	103	173	244	356	643
9	2004	61	113	194	249	365	590
Grade 9 targets		60		168		240	

Selecting Eligible Schools

Given that there are not schools with exactly the target number of students nor with an equal representation of forms, we created synthetic schools to match the targets. This was done by randomly eliminating students from candidate schools. Because small, medium, and large size schools have characteristics other than size that may affect measurement accuracy (e.g., smaller schools may be more homogeneous), only schools near the target size were considered eligible for the analyses. Certainly, schools could be no smaller than the target size. Selection of the maximum size eligible for the analysis was a trial and error process. In each case, we tried to balance having enough schools for stable Generalizability results without having the

maximum size being subjectively larger than the target size. This was most difficult to achieve for the small middle and high schools. Random selection of students was conducted independently for every grade, subject, and school size combination. Table 9 indicates the ranges of school sizes (target to maximum) that became candidates. The numbers of schools that met each criterion and were used in the Generalizability Theory analysis are presented later.

Table 9
Ranges of candidate school sizes

Grade	Small		Medium		Large	
	Target Size	Max. Size	Target Size	Max. Size	Target Size	Max. Size
3	24	36	60	72	96	120
4	24	36	60	72	96	120
5	24	36	60	72	96	120
6	24	36	60	84	180	240
7	36	60	120	172	240	360
8	36	60	120	172	240	360
9	60	120	168	240	240	643
10	60	120	168	240	240	643
11	60	120	168	240	240	643
12	60	120	168	240	240	643

Estimating Assessment SEMs using Generalizability Theory

After creating synthesized schools at the target student populations, assessment SEMs were calculated using the Generalizability models specified by Hoffman and Wise (2000b, 2001) and repeated in the Appendix. Results for baseline years appear in Table A-4 and the 2002 end-of-cycle results are in Table A-5. The assessment SEMs required for computation of accountability index SEMs are the square roots of the Generalizability Theory absolute error variance estimates. Absolute error was chosen because schools must meet fixed standards. Relative error is inappropriate because making comparisons to other schools does not play a role in classifying schools. Tables A-4 and A-5 also provide other Generalizability results, including relative error variance, total variance, and absolute and relative Generalizability coefficients. The Generalizability coefficients estimate the reliabilities of the school mean test scores for each assessment included in CATS. In general, these reliabilities are in the mid-eighties to mid-nineties and are higher for the larger schools than the smaller schools.

To estimate error variance for the non-academic component of the accountability index, total variance across schools (separately for elementary, middle, and high schools) was calculated and multiplied by 1 minus our assumed reliability of .7. The square root of that result yielded our estimate of non-academic SEM. The same non-academic SEM is used for all school sizes, because normal measurement theory may not apply. That is, large school may have a more difficult time getting accurate data about each of their students than small schools that may counteract the general measurement principle that more data decreases measurement error.

Interpolating Assessment SEMs for School Sizes 10 to 500

In the previous step, assessment SEMs were produced for representative school sizes. In order to increase the precision of the SEMs for schools with student populations at other than the representative sizes, an interpolation procedure was used for each grade/assessment combination. This procedure estimated SEMs for school sizes between 10 and 500 by weighting the distance between any given school size and the representative sizes. More specifically, for each assessment the procedure began with the Generalizability absolute error estimates for the three representative school sizes (small, medium, and large), then:

- For each grade-level (g), assessment (a), and representative size (r), within-school, student-level, error standard deviation (SESD) was estimated from the school-level Generalizability Theory absolute error (AERR), number of forms for the assessment (NF), and number of persons per form (NP) for the representative school size (where NF times NP is representative school size = NRS) and the formula relating variance of means (school scores in this case) to variance of observations (students in this case):

$$SESD_{gar} = \sqrt{AERR_{gar} \times NRS_{gar}} \quad (1)$$

- Interpolate within-school error standard deviations for alternate school sizes (or $SESD_{gan}$, where n stands for an alternate size), where s , m , and l refer to small, medium, and large representative sizes, respectively:

$$\text{If } n \leq NRS_s, \text{ let } SESD_{gan} = SESD_{gas} \quad (2)$$

$$\text{If } NRS_s < n < NRS_m, \text{ let} \quad (3)$$

$$SESD_{gan} = \left((n - NRS_s) \times SESD_{gam} + (NRS_m - n) \times SESD_{gas} \right) \div (NRS_m - NRS_s)$$

$$\text{If } NRS_m \leq n < NRS_l, \text{ let} \quad (4)$$

$$SESD_{gan} = \left((n - NRS_m) \times SESD_{gal} + (NRS_l - n) \times SESD_{gam} \right) \div (NRS_l - NRS_m)$$

$$\text{If } n \geq NRS_l, \text{ let } SESD_{gan} = SESD_{gal} \quad (5)$$

- Finally, student level error standard was use to project back to school level error standard depending on school size:

$$AssessmentSEM_{gan} = SESD_{gan} \div \sqrt{n}. \quad (6)$$

The results of these interpolations was an array of 491 SEMs for each of the 27 grade/subject assessments, including on-demand writing, writing portfolio, and CTBS/5 for both the baseline years and the end-of-cycle years. Note that not all school sizes are expected to be present among Kentucky schools. In a sense, these estimates are “what if” values, with estimates available for any size from 10 to 500 based on the assumptions that (1) schools near the representative sizes are similar in student error variance, and (2) interpolation between sizes follows common assumptions about variances of means (for schools) given variances in the subjects (students) making up the means.

Accountability Index SEMs Computations

A school’s accountability index for the baseline years or for the end of any of the long-term cycles is a two-year weighted average of the assessment scores available for the grades contained within the school. Consequently, SEM in the accountability index can also be computed by appropriately weighting and summing assessment SEMs.

The general formula for calculating the variance of a weighted composite from the separate variances of the individual components of the composite is:

$$\sigma^2_{Composite} = \sum_{i=1}^n w_i^2 \sigma_i^2 + 2 \sum_{i=1}^n \sum_{j=1}^n r_{ij} w_i w_j \sigma_i \sigma_j \quad (7)$$

A composite can be decomposed into its true and error components such that some of the variance terms refer to true score variance and some to error variance. Errors are assumed to be uncorrelated with each other or with true scores, so second term components drop out with respect to error variance terms (i.e., when $r_{ij} = 0$). The resulting formula for an accountability SEM becomes:

$$AccountabilitySEM_{sc} = \sqrt{\sum w_{ac}^2 SEM_{as}^2}, \quad (8)$$

for any given combination of school size (s) and configuration (c), where the summation is over all assessments (a). Table A-6 in the Technical Appendix presents the assessment weights. Note that, except for the K-to-12 configuration, some assessment weights are 0.

With 14 grade configurations and 491 school sizes, 6,784 accountability SEMs were computed for the baseline years and another 6,784 accountability SEMs were computed for the end-of-cycle years. As expected, SEMs vary by both the average number of students in a grade and the number of grades in a school. They range from approximately .5 for schools with large total populations to approximately 2.5 for schools with small total populations. Note that these SEMs are “theoretical.” There are not 6,784 schools in Kentucky, so most of the size-by-configuration cells in the matrix are not applicable to any particular school. Like the assessment SEMs, these accountability SEMs are “what if” values applicable given the same assumptions indicated for the assessment SEMs.

Classification SEM Computations

The above procedures provide “look-up” tables for the various grade-configuration-by-school-size combinations for 2002/2003 and for 2003/2004 accountability SEMs. The next step is the computation of classification SEMs using the tabled values. At this point in the

procedure, computational process requirements exceed the “what if” approach used for assessment and accountability SEMs. There are simply too many potential combinations of classification difference scores and accountability SEMs to create look-up tables, particularly since schools may have changed sizes between the baseline and end of cycle years.² Therefore, each school in the analysis is treated individually in the computation of classification SEMs.

True Target Indexez

Classification SEMs are a weighted function of the error variance in the baseline accountability index and error variance in the end-of-cycle accountability index where the weighting is based on the weighting use to calculate the classification index (i.e., the difference between end-of-cycle index and target). In order to calculate the classification SEM, the formula for the true target classification index is needed. Note that the true target index is not shown on the School Growth Chart or used to classify schools. On the other hand, SEM is a statistic about true scores. Therefore, the true target computations are required. Once again, there are two computations, one for the goal line and one for the assistance line. In addition, computation of the true target indexes themselves will be required in a later step of the overall process for calculating classification accuracy.

True Goal Target

The true goal target lies on the line connecting the baseline index (BI) in the year 2000 to the constant value of 100 in 2014. The slope of the line is:

$$Goalslope = (100 - BI) \div (2014 - 2000). \quad (9)$$

Therefore, the true target goal at the end of any cycle, where cycles (C) begins with Cycle 1 in 2002 is:

$$TG_c = BI + 2C((100 - BI) \div 14) = BI(1 - (2C \div 14)) + (200 \div 14)C, \quad (10)$$

which can be interpreted as a weighted function of the baseline accountability index plus a constant.

True Assistance Target

The assistance target for Cycle 1 ending in 2002 is simply the baseline index. For cycles 2 through 7, the true assistance line begins at the value of the baseline index plotted at 2002 and ends at 80 in 2014. The slope of this line is:

$$Asstslope = (80 - BI) \div (2014 - 2002). \quad (11)$$

Therefore, the true assistance target at the end of any cycle, where cycles (C) begin with Cycle 2 in 2004 is:

$$TA_c = BI + 2(C - 1)((80 - BI) \div 12) = BI(1 - (2(C - 1) \div 12)) + (160 \div 12)(C - 1), \quad (12)$$

that can also be interpreted as a weighted function of the baseline accountability index plus a constant.

² If schools change configurations, special index computation rules apply frequently involving use of district level scores. These types of schools have been excluded.

Classification and Classification SEM

Ignoring for the moment the baseline safety net, school classification is based on the difference between a school's targets (goal and assistance) and its obtained scores:

- Positive differences from the goal indicate membership in the Meeting Goal category.
- Negative differences from the Assistance target indicate membership in the Assistance category.
- Negative differences from the goal coupled with positive differences from the Assistance target indicate membership in the Progressing category.

Calculation of classification SEMs requires only straightforward application of the formula for variance of a weighted composite, recognizing that the error variance terms are assumed to be uncorrelated. Therefore, classification accuracy for Meeting Goal versus the two lower categories is a function of error variance in the difference between TG_c and the end of cycle index (AI_c):

$$ClassificationSEM_G = \sqrt{SEM_{AI}^2 + (1 - (2C \div 14))^2 \times SEM_{BI}^2}, \quad (13)$$

where references to school size and configuration for SEMs are assumed, but not shown, and the subscript G refers to errors of measurement around the goal line.

In 2014 (the seventh cycle) the target for all schools is fixed at 100 and the weight for the error term reduces to 0. Error in the index goal decreases from its initial level in 2002 until it is 0 in 2014.

Classification accuracy for Assistance versus the upper categories is a function of error variance in the difference between TA_c and the end of cycle Index (AI_c). Under the rules for computing the assistance target, in Cycle 1 the target equals the baseline accountability index. Therefore, the classification SEMs can be estimated as:

$$ClassificationSEM_A = \sqrt{SEM_{AI}^2 + SEM_{BI}^2}, \quad (14)$$

where reference to school size and configuration for SEMs are assumed, but not shown, and the subscript A refers to errors measurement associated with application of the assistance line.

For the remaining cycles, the computation incorporates a weight on the baseline error term:

$$ClassificationSEM_A = \sqrt{SEM_{AI}^2 + (1 - (2(C - 1) \div 12))^2 \times SEM_{BI}^2}, \quad (15)$$

where references to school size and configuration for SEMs are assumed, but not shown, and the subscript A refers to errors of measurement associated with application of the Assistance line.

Note that, in 2014 (the seventh cycle) the Assistance target for all schools is fixed at 80 and the weight of the Assistance error term reduces to 0.

Shift from Standard Error to Probability Matrices

At this point, for each school eligible for the analysis, we have computed SEM for the difference scores (one for goal and one for assistance) used to classify schools. Standard errors of measurement is an index of the likely variation of observed scores around any given true score. In other words, SEM is the expected distribution of observed scores conditional on true score. Because of the effect of size and configuration on error, difference SEMs are computed for different combinations of school size and grade configuration. The same classification SEM will be computed for all schools with the same size and configuration; however, schools with the same size and configurations cannot be expected to have the same true classification difference. While individual schools have become our vehicle for determining the set of sizes and configurations for computing classification SEMs, the SEMs produced are not particularly meaningful to the individual schools because their true classification differences are unknown. Far more useful at the individual school level is the estimate of the variation in true classification differences that is expected given any particular observed classification difference. Figure 2, presented in the overview, shows the schema for making the translation. The approach uses discrete score ranges to simplify calculations. A matrix of probabilities is created for various ranges of observed scores, given set ranges for true scores. Another matrix of probabilities for various ranges of true scores, given fixed ranges for observed scores, is then created using Bayes' Theorem and estimates of true difference probabilities.

Creating Probability Matrix of Observed Differences Given Possible True Differences

The matrices concern difference scores with 0 being the critical decision point, making 0 one of the required interval boundaries. After examining the range of differences between observed index scores and target index scores for goal and for assistance classification decisions, the range of differences was divided into 54 intervals. These intervals included (a) all scores less than -13, (b) all greater than +13, plus (c) the remaining 52 intervals between -13 and +13 with the width of each interval equal to .5. These same score intervals were also used for possible observed scores. For any cell in the resulting matrix, SEM values were used to calculate the probability of the identified observed difference, given the identified true difference. Calculations are based on the standard assumption that errors around any given true difference are normally distributed with standard deviation equal to the SEM.

Estimating of True Index Variance

An observed assessment score is the result of a "true" score and measurement error. Likewise, variance in observed scores is a function of variance in true scores and variance in error. Since $(SEM)^2$ is an estimate of error variance, estimates of true variance are calculated by subtracting error variance from total score variance. Since the magnitude of error variance is likely a function of school size and school configuration, we assume total variance is as well. Therefore, we investigated variance in observed classification difference scores by school size and configuration.

Calculating Total Variance in Classification Difference Scores and School Size

In order to calculate score variance, multiple observations must be available. To create these multiple observations, schools were grouped by rounding their sizes for 2003-2004 to the nearest 25 for schools up to 300. Above 300 students per grade, schools were categorized as either 350 or 450 students per grade. Variance in classification differences for both goal and assistance targets were calculated for each of these groups. The results are plotted in Figure 3 and 4. Each figure also displays the fit of a power function to school size. The fit is very close in both cases as noted by the R^2 of .84 and .88 for the goal and assistance classification difference standard deviations, respectively. Given the strength of the relationship between size and variance in observed classification difference scores, using these size categories to estimate variance estimates is warranted. In contrast, there was no discernable pattern to the classification standard deviations for the different configurations and several of the configurations contains so few schools that estimated standard deviations were either not possible or potentially unstable.

Estimating Distributions of True Differences

Having established estimates of total variance that can be applied to schools of any given size and having calculated error variance estimates for each school given its size and configuration, true variance estimates applicable for each school were calculated as the difference between the two. The next step was to use these true variance estimates to calculate probabilities of school true scores being in any of the scores intervals (-13 to +13). Computation of the array of true difference probabilities is based on the assumption of normally distributed scores centered on the mean of the differences with a standard deviations equal to the true variance estimation. True mean differences were estimated by observed mean differences, and like total variance, mean differences were estimated separately for school size category. Figure 5 and 6 show that strength of the relationship between size and mean difference as capture by second-degree polynomial equations. Again, use of school size to capture difference means appears appropriate. Note that these true difference probability arrays are dependent on school size and configuration, but they are not yet conditioned on school observed score. That is the next step.

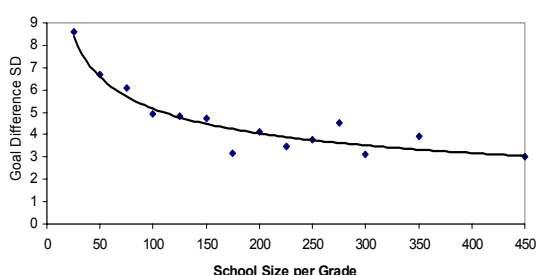


Figure 3. Classification difference standard deviations for Meeting Goal by school size.

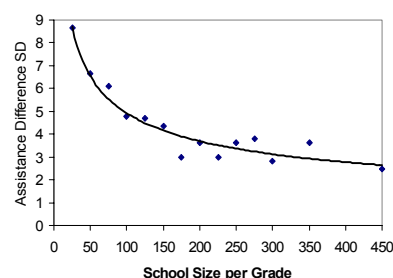


Figure 4. Classification difference standard deviations for Assistance by school size.

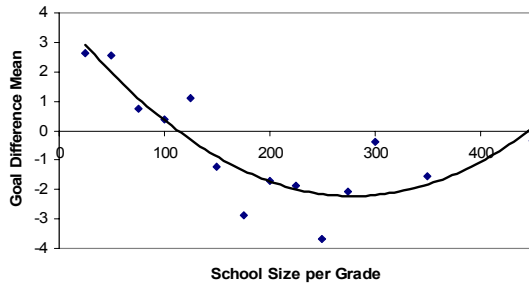


Figure 5. Classification difference means for meeting goal by school size.

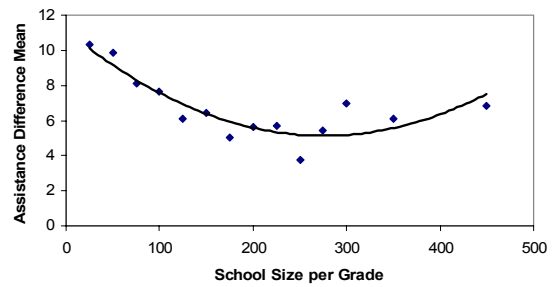


Figure 6. Classification difference means for assistance by school size.

Creating Matrix of Probabilities of True Differences Given Observed Difference

Once again, for each school, two matrices of probabilities of observed classification differences given true differences were calculated, one for goal decisions and one for assistance decisions. Likewise two arrays of probabilities of true differences are created for each school. For a given observed difference the probability of classification true difference in a given interval is:

$$P(\text{True}_i|\text{Obs}_j) = \frac{P(\text{Obs}_j|\text{True}_i)P(\text{True}_i)}{P(\text{Obs}_j|\text{True}_1)P(\text{True}_1)+P(\text{Obs}_j|\text{True}_2)P(\text{True}_2)+P(\text{Obs}_j|\text{True}_3)P(\text{True}_3)+\dots+P(\text{Obs}_j|\text{True}_k)P(\text{True}_k)} \quad (16)$$

where Obs_j = observed difference represented by interval j , with k possible difference intervals, and True_i = true difference represented by interval i , with k intervals represented in the probability matrix.

Bayes' transformation was applied to the data for each school. The result was a matrix of probabilities of each of the 54 true score intervals being in any of the 54 observed difference intervals, with separate matrices for meeting goal and for needing assistance. Any given school had only one observed goal difference and one observed assistance difference; therefore, only one column of either school-specific $\text{Prob}(\text{True}|\text{Observed})$ matrix was relevant.³ For each school, the observed column containing the school's observed difference was identified for both the goal and assistance matrices. Appropriate summation of cell probabilities above and below zero (described earlier) provide estimates of the probabilities of the school having a true classification in Meeting Goal and in Assistance. From these two estimates, an estimate of the probability of the school having a true classification in Progressing was computed.

Summarize Probabilities Across Schools

The final step was to summarize probabilities across school by computing mean probabilities of each of the three classifications (Meeting Goal, Progressing, and Assistance) for the observed classifications of schools (Figure 1), for the classification of school if no safety

³ "School-specific" is not exactly correct. All schools of a given grade configuration whose sizes were identical in the base years and in the final years will have the same probability matrix.

were applied (Figure 2), and for the joint categorization that results from considering classification with and without the safety net (Figure 3).

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Appendix Technical Documentations

Generalizability Models

Standard errors of measure of the various components of the accountability model are estimated by Generalizability analyses of students' NAPD scores. Given that school index scores span two years, the basic model is one in which pupils are nested within forms, years, and schools, and forms are nested within years and are crossed with schools. For writing and for CTBS/5 forms are not a consideration, so the Generalizability model is reduced to one in which pupils are nested within schools and years.

Figure A-1 presents the four-facet design for the Kentucky Core Content Tests. Tables A-1, 2 and 3 presents the calculations using Brennan's (1981) notation and algorithms for generating sums of squares and variance components. For each of the grade/subject combinations, the six sources of variance in schools' two-year academic index averages include: (1) school, (2) year, (3) school by year, (4) form within year, (5) school by form within year, and (6) pupil within form within school by form. The order of the nesting terms in the last source of variance is a little ambiguous in its wording since pupils are nested within forms, within schools, and within years. However, for derivation of the error components, the expressed order of the nested does not matter, as long as the nesting is captured.

Random, fixed, or sampled from a finite universe

Generalizability theory explicitly considers the universe to which observed score are interpretable. Typically, the items that make up a particular test are only viewed as samples of an infinite array of similar items. Being sampled from an infinite domain, test items are typically considered "random." On the other hand, some facets may cover the intended universe to which scores are intended to generalize. Year, for example, could be considered fixed because the universe of generalization is two years and both years are sampled. On the other hand, year could be considered as sampled from a finite universe. The logic is this: The school academic index, while directly interpretable as the average of students' achievement, is being used to make inferences about the instructional programs of those schools. An accountability cycle is four years long. Changes in instruction that occur in any of those four years could impact students' achievement in the final two years. Thus, the universe of generalization could be viewed as instructional change that occurred in any of the four years of the cycle. Only two of the four years are assessed, however. Other than being illustrative of sampling within a fixed domain, we are making no strong argument that the present data be treated with years being samples of a fixed four-year domain. Instead, we are suggesting that years be considered fixed. Forms and pupils are assumed to be randomly sampled from a infinite domain. Table A-3 indicates that the value of for two sources of variance (year and school x year) reduce to zero when years are considered fixed.

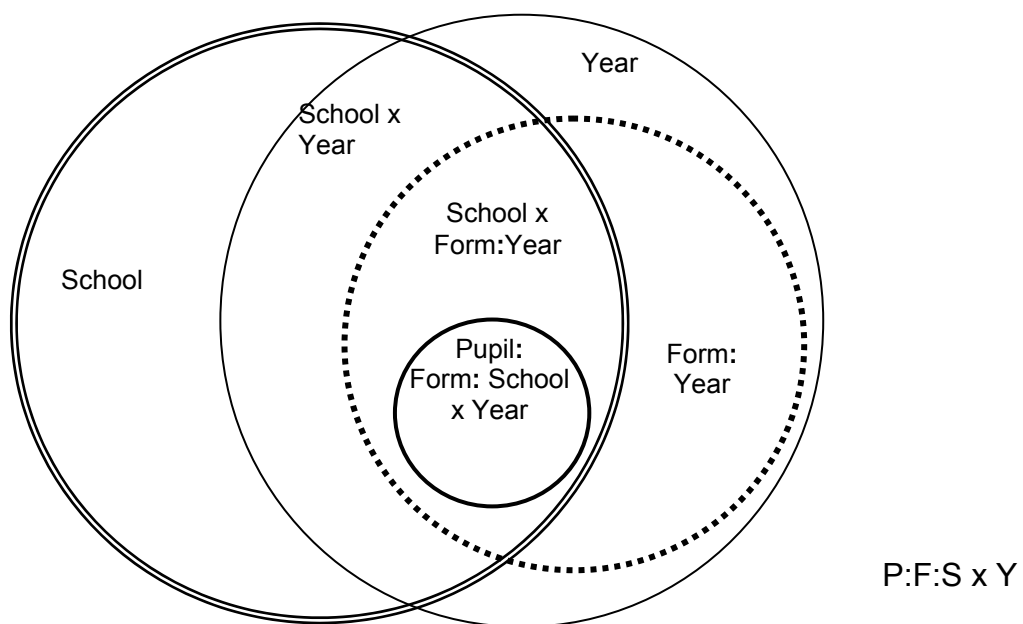


Figure A-1. Generalizability theory design representing Kentucky Core Content Test two-year accountability cycle.

Table A-1
Estimating Variance Components for Pupil: School Year Form Generalizability Theory Design – Random Effects Estimates

Effect	df	Means	SS
School (s)	$n_s - 1$	$\bar{X}_s = \frac{1}{n_y n_f n_p} \sum_y \sum_f \sum_p X_{syfp}$	$n_f n_y n_p \sum \bar{X}_s^2 - n_s n_y n_f n_p \bar{X}^2$
Year (y)	$n_y - 1$	$\bar{X}_y = \frac{1}{n_s n_f n_p} \sum_s \sum_f \sum_p X_{syfp}$	$n_s n_f n_p \sum \bar{X}_y^2 - n_s n_y n_f n_p \bar{X}^2$
School x Year	$(n_s - 1)(n_y - 1)$	$\bar{X}_{sy} = \frac{1}{n_f n_p} \sum_f \sum_p X_{syfp}$	$n_f n_p \sum \sum \bar{X}_{sy}^2 - n_f n_y n_p \sum \bar{X}_s^2 - n_s n_f n_p \sum \bar{X}_y^2 + n_s n_y n_f n_p \bar{X}^2$
Form:Year (f:y)	$n_y(n_f - 1)$	$\bar{X}_{f:y} = \frac{1}{n_s n_p} \sum_s \sum_p X_{syfp}$	$n_s n_p \sum \sum \bar{X}_{yf}^2 - n_s n_f n_p \sum \bar{X}_y^2$
School x Form : Year (sf:y)	$n_y(n_s - 1)(n_f - 1)$	$\bar{X}_{sf:y} = \frac{1}{n_p} \sum_p X_{syfp}$	$n_p \sum \sum \sum \bar{X}_{syf}^2 - n_f n_p \sum \sum \bar{X}_{sy}^2 - n_s n_p \sum \sum \bar{X}_{yf}^2 + n_s n_f n_p \bar{X}_y^2$
Pupil: School Year Form (p:sfy)	$n_y n_s n_f (n_p - 1)$	na	$\sum \sum \sum \sum X_{psyf}^2 - n_p \sum \sum \sum \bar{X}_{syf}^2$
Total	$n_s n_y n_f n_p - 1$	$\bar{X} = \frac{1}{n_s n_y n_f n_p} \sum_s \sum_y \sum_f \sum_p X_{syfp}$	$\sum \sum \sum \sum X_{psyf}^2 - n_s n_y n_f n_p \bar{X}^2$

Table A-2

Estimating Variance Components for Pupil: School Year Form Generalizability Theory Design – G-Study Estimates

Effect (α)	Estimated σ^2 – Random Effects Model	Estimated $\sigma^2(\alpha M)$ -- Mixed Models (N = Universe size)	
		Basic Mixed Model	Year Fixed
School (s)	$\frac{[MS(s) - MS(sy)]}{n_y n_f n_p}$	$\hat{\sigma}_s^2 + \frac{\hat{\sigma}_{sv}^2}{N_y} + \frac{\hat{\sigma}_{sf:y}^2}{N_f N_y} + \frac{\hat{\sigma}_{p:fsy}^2}{N_f N_y N_p}$	$\hat{\sigma}_s^2 + \frac{\hat{\sigma}_{sv}^2}{N_y}$
Year (y)	$\frac{[MS(y) - MS(sy) - MS(fy) + MS(sfy)]}{n_s n_f n_p}$	$\hat{\sigma}_y^2 + \frac{\hat{\sigma}_{sv}^2}{N_s} + \frac{\hat{\sigma}_{f:y}^2}{N_f} + \frac{\hat{\sigma}_{sf:y}^2}{N_s N_f} + \frac{\hat{\sigma}_{p:fsy}^2}{N_s N_f N_p}$	$\hat{\sigma}_y^2$
School x Year	$\frac{[MS(sy) - MS(sfy)]}{n_f n_p}$	$\hat{\sigma}_{sy}^2 + \frac{\hat{\sigma}_{sf:y}^2}{N_f} + \frac{\hat{\sigma}_{p:fsy}^2}{N_f N_p}$	$\hat{\sigma}_{sy}^2$
Form:Year (f:y)	$\frac{[MS(fy) - MS(sfy)]}{n_s n_p}$	$\hat{\sigma}_{f:y}^2 + \frac{\hat{\sigma}_{sf:y}^2}{N_s} + \frac{\hat{\sigma}_{p:fsy}^2}{N_s N_p}$	$\hat{\sigma}_{f:y}^2$
School x Form : Year (sf:y)	$\frac{[MS(sfy) - MS(syfp)]}{n_p}$	$\hat{\sigma}_{f:sy}^2 + \frac{\hat{\sigma}_{p:fsy}^2}{N_p}$	$\hat{\sigma}_{f:sy}^2$
Pupil: School Year Form (p:sfy)	MS(syfp)	$\hat{\sigma}_{p:fsy}^2$	$\hat{\sigma}_{p:fsy}^2$

Table A-3

Estimating Variance Components for Pupil: School Year Form Generalizability Theory Design – D-study Estimates

Effect (α)	D-study error component	Use term in	
		Absolute error estimate	Relative error estimate
School (s)	$\hat{\sigma}_s^2 + \frac{\hat{\sigma}_{sv}^2}{N_y}$		
Year (y)	$[\hat{\sigma}_y^2 / N_y] [1 - \frac{n_y}{N_y}] = 0$	(X)	
School x Year	$[\hat{\sigma}_{sy}^2 / N_y] \times [1 - \frac{n_y}{N_y}] = 0$	(X)	(X)
Form:Year (f:y)	$\hat{\sigma}_{f:y}^2 / N_y N_f$	X	
School x Form : Year (sf:y)	$\hat{\sigma}_{f:sy}^2 / N_y N_f$	X	X
Pupil: School Year Form (p:sfy)	$\hat{\sigma}_{p:fsy}^2 / N_y N_f n_p$	X	X

Note that current literature is mixed on whether pupils should be considered fixed, random, or sampled from a fixed domain (Cronbach, Linn, Brennan, & Haertel, 1997; Hambleton, Jaeger, Koretz, Linn, Millman, & Phillips, 1996; Yen, 1997). Persistent criticisms of Kentucky's accountability model that cohort-to-cohort variation in student proficiency is unfair (Hoffman, 1998) makes treating students as fixed unwise. Yen uses two different approaches, one for which students are random, and a second for which students are treated as samples of a finite domain with that domain being defined as the total school population from which the tested students are taken. Yen's second approach does not fit Kentucky's two year cycle very well, particularly since we know the transience among students is perceived to be a significant issue for some districts (Thacker, Koger, Hoffman, and Koger, 2000) and is indeed related to school scores (Medsker, 1998). Therefore, we have chosen to treat students as random, i.e., sampled from an infinite universe. (Note also that in Yen's second approach, she adds a term for measurement error at the person level. That term is mathematically eliminated when students are treated as random.)

Yen (1997) also discussed potential modification to the forms by schools interaction given that forms are intended to target slightly different content. She concludes that since there is no way to directly test differences in targets (forms and students are confounded), the straightforward approach, as presented in Tables 2 – 4, is more acceptable with a caveat that it may overestimate standard error.

Absolute and relative error

Generalizability theory considers two kinds of error: absolute and relative. Absolute error is appropriate to consider when the objects of measure (schools in our case) are being assessed against a standard that generalizes beyond any of the particular instances of the various facets of measurement (e.g., different forms, different years, different pupils). Relative error, on the other hand, is appropriate when schools are being compared to each other and have been subject to the same measurement processes (same forms, same years). Table A-3 indicates which variance components enter each type of error estimate. With years treated as fixed, three error components (form within year, school by form within year, and pupil within form within school by form) are summed to estimate absolute error. Only the later two components (school by form within year, and pupil within form within school by form) are summed to estimate error variance for the relative model. Because schools are being assessed against a standard, rather than by relative standing among other schools, absolute error is the appropriate estimate to use in computing CATS classification accuracy.

Special Considerations for Writing Assessments

Each student completes one on-demand writing prompt, and it is chosen by the student from a pair of alternatives. Six pairs of writing prompts constitute six forms for on-demand writing. From past analysis (Hoffman, Koger, & Awbrey, 1997), we know that means for different writing prompts vary greatly for prompts within a form as well as for prompts from different forms. The variation in means leads to the conclusion that each prompt should be treated as a separate "form" using the same Generalizability analysis design described above. As far as the self-selection factor is concerned, we see no option other than considering it one of the random factors affecting prompt (i.e., item) sampling.

Portfolios, however, are (in theory⁴) unique to each individual student. “Forms” as a theoretical facet for portfolios is confounded with students.⁵ Therefore, school-level error variance for portfolios will be assessed using a Generalizability design similar to the one presented above, but without form as a facet. That is, pupils are nested within the intersection of schools and years. Formulas for this three facet (pupils:schools x years) are available in Brennan (1981), designated as i:(p x h) in his notation.

CTBS/5

CTBS/5 scores also do not include separate forms at any one of the grade levels in which it is administered. Therefore the same Generalizability model applied to writing portfolios is applied to CTBS/5 scores.

⁴ Some schools do tend to structure common activities and present selected topics for students to create portfolio entries.

⁵ Again, this is an oversimplification. Anecdotally, some schools reportedly have been doing a better job than others of structuring portfolio activities that facilitate higher quality writing. “Item sampling,” therefore, may be confounded with schools. In this unusual case, schools become both the object of measurement and an instrument, or facet, of measurement.

Table A-4
Variance Components for Each Grade/Subject By School size Configuration for baseline 1999-2000

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies			Lg = Large School Md = Medium School Sm = Small School		NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years		Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance		Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability		
Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
3	ct	lg	66	96	2	.	11.935	11.935	281.277	0.958	0.958
3	ct	md	35	60	2	.	18.568	18.568	406.480	0.954	0.954
3	ct	sm	49	24	2	.	48.407	48.407	275.457	0.824	0.824
4	rd	lg	36	16	2	6	6.208	5.995	101.721	0.939	0.941
4	rd	md	55	10	2	6	8.106	8.028	140.524	0.942	0.943
4	rd	sm	44	4	2	6	22.325	21.798	75.395	0.704	0.711
4	sc	lg	36	16	2	6	6.119	6.119	110.375	0.945	0.945
4	sc	md	55	10	2	6	7.821	7.821	182.917	0.957	0.957
4	sc	sm	44	4	2	6	18.186	17.839	108.250	0.832	0.835
4	wod	lg	35	16	2	6	5.651	5.512	44.072	0.872	0.875
4	wod	md	54	10	2	6	7.972	7.896	52.788	0.849	0.850
4	wod	sm	42	4	2	6	15.894	15.867	47.132	0.663	0.663
4	wp	lg	54	96	2	.	4.048	4.048	147.104	0.972	0.972
4	wp	md	29	60	2	.	6.090	6.090	199.888	0.970	0.970
4	wp	sm	51	24	2	.	17.683	17.683	227.601	0.922	0.922
5	ah	lg	28	8	2	12	8.067	7.939	143.255	0.944	0.945
5	ah	md	39	5	2	12	10.796	10.459	119.436	0.910	0.912
5	ah	sm	28	2	2	12	22.270	22.175	85.604	0.740	0.741
5	ma	lg	33	16	2	6	7.364	7.186	200.391	0.963	0.964
5	ma	md	57	10	2	6	9.426	9.426	178.516	0.947	0.947
5	ma	sm	39	4	2	6	22.213	22.213	145.874	0.848	0.848
5	pl	lg	28	8	2	12	8.868	8.632	142.296	0.938	0.939
5	pl	md	38	5	2	12	12.913	12.737	131.288	0.902	0.903
5	pl	sm	28	2	2	12	31.440	31.440	156.133	0.799	0.799
5	ss	lg	32	16	2	6	8.144	8.144	229.568	0.965	0.965
5	ss	md	57	10	2	6	12.491	12.312	199.534	0.937	0.938
5	ss	sm	39	4	2	6	27.197	26.125	199.494	0.864	0.869
6	ct	lg	36	180	2	.	6.494	6.494	159.455	0.959	0.959
6	ct	md	42	60	2	.	18.344	18.344	335.471	0.945	0.945
6	ct	sm	41	24	2	.	49.311	49.311	181.653	0.729	0.729
7	rd	lg	41	40	2	6	2.293	2.205	122.577	0.981	0.982
7	rd	md	22	20	2	6	4.428	4.230	49.878	0.911	0.915
7	rd	sm	28	6	2	6	12.799	12.799	107.816	0.881	0.881
7	sc	lg	41	40	2	6	3.591	3.571	173.255	0.979	0.979
7	sc	md	22	20	2	6	7.215	7.215	80.072	0.910	0.910
7	sc	sm	28	6	2	6	15.238	14.478	187.607	0.919	0.923

Table A-4
Variance Components for Each Grade/Subject By School size Configuration for baseline 1999-2000

Variance Components for Each Grade/Subject By School Size Configuration for Baseline 1999-2000											
rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies			Lg = Large School Md = Medium School Sm = Small School		NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years			Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance		Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability	
Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
7	wod	lg	41	40	2	6	2.510	2.260	64.101	0.961	0.965
7	wod	md	22	20	2	6	4.330	4.249	30.428	0.858	0.860
7	wod	sm	27	6	2	6	11.789	11.789	75.778	0.844	0.844
7	wp	lg	48	240	2	.	1.733	1.733	148.413	0.988	0.988
7	wp	md	27	120	2	.	3.700	3.700	69.190	0.947	0.947
7	wp	sm	36	36	2	.	12.672	12.672	120.415	0.895	0.895
8	ah	lg	29	20	2	12	3.241	3.208	126.937	0.974	0.975
8	ah	md	26	10	2	12	6.147	6.061	106.441	0.942	0.943
8	ah	sm	21	3	2	12	17.900	17.649	270.439	0.934	0.935
8	ma	lg	40	40	2	6	2.484	2.446	128.201	0.981	0.981
8	ma	md	27	20	2	6	4.868	4.781	79.019	0.938	0.939
8	ma	sm	26	6	2	6	13.543	13.543	345.025	0.961	0.961
8	pl	lg	30	20	2	12	3.398	3.356	108.562	0.969	0.969
8	pl	md	26	10	2	12	7.395	7.356	104.654	0.929	0.930
8	pl	sm	20	3	2	12	22.297	22.297	257.481	0.913	0.913
8	ss	lg	41	40	2	6	3.185	3.185	108.854	0.971	0.971
8	ss	md	27	20	2	6	5.375	5.191	109.991	0.951	0.953
8	ss	sm	26	6	2	6	12.817	12.455	273.806	0.953	0.955
9	ct	lg	46	312	2	.	4.143	4.143	327.514	0.987	0.987
9	ct	md	36	168	2	.	7.733	7.733	236.606	0.967	0.967
9	ct	sm	36	24	2	.	53.091	53.091	305.827	0.826	0.826
10	pl	lg	47	20	2	12	3.276	3.190	106.937	0.969	0.970
10	pl	md	29	14	2	12	5.655	5.495	65.694	0.914	0.916
10	pl	sm	26	5	2	12	12.844	12.844	65.829	0.805	0.805
10	rd	lg	56	40	2	6	2.392	2.338	102.136	0.977	0.977
10	rd	md	39	28	2	6	3.839	3.748	61.919	0.938	0.939
10	rd	sm	29	10	2	6	8.099	8.099	65.020	0.875	0.875
11	ah	lg	35	20	2	12	3.443	3.365	161.583	0.979	0.979
11	ah	md	24	14	2	12	4.278	4.218	101.996	0.958	0.959
11	ah	sm	34	5	2	12	10.347	10.321	102.731	0.899	0.900
11	ma	lg	40	40	2	6	3.068	2.840	168.993	0.982	0.983
11	ma	md	27	28	2	6	3.814	3.750	172.664	0.978	0.978
11	ma	sm	38	10	2	6	9.492	9.249	102.219	0.907	0.910
11	sc	lg	40	40	2	6	2.923	2.754	96.554	0.970	0.971
11	sc	md	27	28	2	6	3.194	2.849	78.908	0.960	0.964
11	sc	sm	38	10	2	6	7.591	7.519	74.248	0.898	0.899
11	ss	lg	40	40	2	6	2.352	2.310	140.559	0.983	0.984
11	ss	md	27	28	2	6	2.871	2.753	99.381	0.971	0.972

Table A-4

Variance Components for Each Grade/Subject By School size Configuration for baseline 1999-2000

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies			Lg = Large School Md = Medium School Sm = Small School		NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years		Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance		Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability		
School			Absol.				Total		Absol.		Rel.
Grade	Subject	Size	NS	NP	NY	NF	Err.	Rel. Err.	Var.	Gen.	Gen.
11	ss	sm	38	10	2	6	7.874	7.874	75.181	0.895	0.895
12	wod	lg	29	40	2	6	1.673	1.606	21.860	0.923	0.927
12	wod	md	29	28	2	6	2.853	2.636	37.943	0.925	0.931
12	wod	sm	29	10	2	6	6.263	6.263	40.971	0.847	0.847
12	wp	lg	36	240	2	.	1.991	1.991	61.669	0.968	0.968
12	wp	md	50	168	2	.	3.002	3.002	82.675	0.964	0.964
12	wp	sm	42	60	2	.	7.959	7.959	92.523	0.914	0.914

Table A-5
Variance Components for Each Grade/Subject By School size Configuration for End-of-Cycle 2003-2004

Variance Components for Each Grade/Subject By School Size Configuration for End-of-Cycle 2003-2004

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability							
Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
3	ct	lg	45	96	2	.	10.004	10.004	167.919	0.940	0.940
3	ct	md	41	60	2	.	17.007	17.007	230.608	0.926	0.926
3	ct	Sm	43	24	2	.	42.384	42.384	218.827	0.806	0.806
4	rd	lg	33	16	2	6	4.495	4.495	88.967	0.949	0.949
4	rd	md	19	10	2	6	7.694	7.507	77.002	0.900	0.903
4	rd	sm	30	4	2	6	17.789	17.576	96.630	0.816	0.818
4	sc	lg	33	16	2	6	4.910	4.885	135.920	0.964	0.964
4	sc	md	19	10	2	6	8.049	7.815	82.432	0.902	0.905
4	sc	sm	30	4	2	6	16.599	16.555	145.675	0.884	0.885
4	wd	lg	27	16	2	6	6.728	4.522	52.716	0.872	0.914
4	wd	md	10	10	2	6	7.873	7.175	77.972	0.899	0.908
4	wd	sm	29	4	2	6	16.675	14.167	81.602	0.796	0.826
4	wp	lg	44	96	2	.	2.835	2.835	128.416	0.978	0.978
4	wp	md	33	60	2	.	4.561	4.561	154.237	0.970	0.970
4	wp	sm	36	24	2	.	13.508	13.508	195.878	0.931	0.931
5	ah	lg	25	8	2	12	7.662	7.373	140.308	0.945	0.947
5	ah	md	5	5	2	12	15.628	15.628	348.627	0.955	0.955
5	ah	sm	27	2	2	12	20.184	20.184	167.725	0.879	0.879
5	ma	lg	34	16	2	6	7.172	7.172	163.811	0.956	0.956
5	ma	md	17	10	2	6	10.968	10.968	168.182	0.935	0.935
5	ma	sm	30	4	2	6	25.342	24.848	173.636	0.854	0.858
5	pl	lg	25	8	2	12	6.817	6.604	107.239	0.936	0.938
5	pl	md	5	5	2	12	12.105	12.105	220.741	0.945	0.945
5	pl	sm	27	2	2	12	28.768	28.561	156.052	0.816	0.817
5	ss	lg	34	16	2	6	6.665	6.661	177.193	0.962	0.962
5	ss	md	17	10	2	6	12.202	12.202	204.863	0.940	0.940
5	ss	sm	30	4	2	6	26.709	26.709	158.571	0.832	0.832
6	ct	lg	46	180	2	.	6.343	6.343	267.664	0.976	0.976
6	ct	md	30	60	2	.	18.418	18.418	190.093	0.903	0.903
6	ct	sm	32	24	2	.	44.544	44.544	196.381	0.773	0.773
7	rd	lg	48	40	2	6	1.932	1.738	69.626	0.972	0.975
7	rd	md	18	20	2	6	3.696	8.696	75.975	0.951	0.951
7	rd	sm	29	6	2	6	11.156	10.735	140.306	0.920	0.923
7	sc	lg	48	40	2	6	3.366	3.243	137.861	0.976	0.976
7	sc	md	18	20	2	6	5.818	5.398	191.637	0.970	0.972
7	sc	sm	29	6	2	6	17.805	17.629	274.434	0.935	0.936

Table A-5
Variance Components for Each Grade/Subject By School size Configuration for End-of-Cycle 2003-2004

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies			Lg = Large School Md = Medium School Sm = Small School		NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years		Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance		Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability		
Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
7	wo	lg	55	16	2	6	4.332	4.131	50.258	0.914	0.918
7	wo	md	27	10	2	6	5.981	5.795	53.171	0.888	0.891
7	wo	sm	5	6	2	6	11.690	10.302	62.701	0.814	0.836
7	wp	lg	58	240	2	.	1.842	1.842	188.371	0.990	0.990
7	wp	md	24	120	2	.	3.654	3.654	112.742	0.968	0.968
7	wp	sm	38	36	2	.	12.586	12.586	146.029	0.914	0.914
8	ah	lg	43	20	2	12	3.930	3.719	147.862	0.973	0.975
8	ah	md	16	10	2	12	6.772	6.689	220.781	0.969	0.970
8	ah	sm	19	3	2	12	19.489	19.372	320.170	0.939	0.940
8	ma	lg	49	40	2	6	2.696	2.563	126.443	0.979	0.980
8	ma	md	18	20	2	6	4.975	4.975	139.513	0.964	0.964
8	ma	sm	35	6	2	6	14.672	14.672	259.975	0.944	0.944
8	pl	lg	43	20	2	12	3.711	3.663	96.383	0.962	0.962
8	pl	md	16	10	2	12	6.611	6.340	137.607	0.952	0.954
8	pl	sm	19	3	2	12	18.345	18.214	211.639	0.913	0.914
8	ss	lg	49	40	2	6	3.286	3.088	123.386	0.973	0.975
8	ss	md	18	20	2	6	4.758	4.758	133.005	0.964	0.964
8	ss	sm	35	6	2	6	15.580	14.855	183.452	0.915	0.919
9	ct	lg	80	240	2	.	5.397	5.397	249.632	0.978	0.978
9	ct	md	43	168	2	.	7.846	7.846	180.539	0.957	0.957
9	ct	sm	33	42	2	.	30.178	30.178	245.419	0.877	0.877
10	pl	lg	54	20	2	12	3.814	3.681	82.298	0.954	0.955
10	pl	md	17	14	2	12	5.495	5.344	79.838	0.931	0.933
10	pl	sm	28	5	2	12	13.546	13.380	123.802	0.891	0.892
10	rd	lg	59	40	2	6	3.072	2.677	126.643	0.976	0.979
10	rd	md	25	28	2	6	3.432	3.249	80.403	0.957	0.960
10	rd	sm	32	10	2	6	9.791	9.383	121.608	0.919	0.923
11	ah	lg	36	20	2	12	4.498	4.400	175.102	0.974	0.975
11	ah	md	22	14	2	12	6.245	6.052	130.195	0.952	0.954
11	ah	sm	30	5	2	12	14.428	14.251	164.812	0.912	0.914
11	ma	lg	39	40	2	6	3.473	3.352	157.860	0.978	0.979
11	ma	md	28	28	2	6	4.532	4.261	130.999	0.965	0.967
11	ma	sm	34	10	2	6	11.721	11.656	143.732	0.918	0.919
11	sc	lg	39	40	2	6	2.725	2.534	70.717	0.961	0.964
11	sc	md	28	28	2	6	3.253	3.052	64.424	0.950	0.953
11	sc	sm	34	10	2	6	9.634	9.634	96.570	0.900	0.900
11	ss	lg	39	40	2	6	3.603	3.255	136.390	0.974	0.976
11	ss	md	28	28	2	6	4.495	4.197	98.326	0.954	0.957

Table A-5

Variance Components for Each Grade/Subject By School size Configuration for End-of-Cycle 2003-2004

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies			Lg = Large School Md = Medium School Sm = Small School		NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years			Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance		Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability	
		School					Absol.		Total	Absol.	Rel.
Grade	Subject	Size	NS	NP	NY	NF	Err.	Rel. Err.	Var.	Gen.	Gen.
11	ss	sm	34	10	2	6	10.489	10.126	119.414	0.912	0.915
12	wo	lg	14	38	2	6	2.398	1.580	46.627	0.952	0.968
12	wo	md	12	26	2	6	3.071	2.855	51.158	0.940	0.944
12	wo	sm	24	9	2	6	15.875	7.903	73.014	0.783	0.892
12	wp	lg	39	123	2	.	13.848	13.848	223.017	0.938	0.938
12	wp	md	35	86	2	.	17.765	17.765	227.747	0.922	0.922
12	wp	sm	43	31	2	.	54.895	54.895	267.423	0.795	0.795

Weights used in Calculating accountability index Score and accountability index SEMs

Table A-6 Weight used in Calculating accountability index Score and accountability index SEMs

Grade	Subject	WK 5	WK 6	WK 8	WK 12	W4 5	W4 6	W4 8	W6 8	W6 12	W7 8	W7 9	W7 12	W9 12	W10 12
03	ct	.050000	.025000	.025000	.016667										
04	rd	.190000	.190000	.095000	.063333	.200000	.190000	.100000							
04	sc	.142500	.142500	.071250	.047500	.150000	.142500	.075000							
04	wod	.028500	.028500	.014250	.009500	.030000	.028500	.015000							
04	wp	.114000	.114000	.057000	.038000	.120000	.114000	.060000							
05	ah	.047500	.047500	.023750	.015833	.050000	.047500	.025000							
05	ma	.190000	.190000	.095000	.063333	.200000	.190000	.100000							
05	na	.047500	.047500	.023750	.015833	.050000	.047500	.025000							
05	pl	.047500	.047500	.023750	.015833	.050000	.047500	.025000							
05	ss	.142500	.142500	.071250	.047500	.150000	.142500	.075000							
06	ct		.025000	.025000	.016667		.050000	.025000	.050000	.025000					
07	rd			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
07	sc			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
07	wod			.014250	.009500			.014250	.028500	.014250	.030000	.028500	.015000		
07	wp			.057000	.038000			.057000	.114000	.057000	.120000	.114000	.060000		
08	ah			.035625	.023750			.035625	.071250	.035625	.075000	.071250	.037500		
08	ma			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
08	na			.047500	.031667			.047500	.095000	.047500	.100000	.095000	.050000		
08	pl			.035625	.023750			.035625	.071250	.035625	.075000	.071250	.037500		
08	ss			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
09	ct				.016667					.025000		.050000	.025000	.050000	
10	pl				.023750					.035625			.035625	.071250	.075000
10	rd				.047500					.071250			.071250	.142500	.150000
11	ah				.023750					.035625			.035625	.071250	.075000
11	ma				.047500					.071250			.071250	.142500	.150000
11	sc				.047500					.071250			.071250	.142500	.150000
11	ss				.047500					.071250			.071250	.142500	.150000
12	na				.031667					.047500			.047500	.095000	.100000
12	wod				.009500					.014250			.014250	.028500	.030000
12	wp				.038000					.057000			.057000	.114000	.120000

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